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FLOWER RECOGNITION USING CNN IN MACHINE LEARNING

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Abstract : In an era of increasingly advanced technology, including artificial intelligence in solving real-world problems makes most of the impossible possible. Introducing machine learning algorithms such as convolutional neural networks to identify flower species in images can be of great help to industries such as pharmaceuticals and cosmetics. In this study, we perform image recognition to improve accuracy and specific identification of repeating colors that are similar in appearance. We use aconvolutional neural network for instinctive recognition based on flower images. Convolutional neural networks play animportant role in color image identification. Each species has different characteristics such as texture, petals, and shape of the sepals. The proposed method can be one of the most promising solutions for developing image-based retrieval applications inthe fields of plant classification environmental monitoring system, or multimedia communities.

IndexTerms- Convolutional Neural Network,Machine Learning, Dataset, Training and Testing Set, Anaconda jupyter Notobook, Tensorflow, Flower Recognition. **Introduction**

Flower recognition using convolutional neural networks (CNNs) is an interesting field of research and practice. Applied tothe field of computer vision. CNNs are a type of machine learning model that is particularly suitable for image classificationtasks, making them an ideal choice for recognizing different types of flowers based on their visual characteristics. The goal offlower recognition using CNNs is to train a model that can accurately identify different types of flowers based on uniquefeatures such as color, shape, and texture. This is achieved by providing the CNN model with a large dataset of labeled imagesof different types of flowers, allowing the model to recognize patterns and features specific to each type of flower. Flowerrecognition has a variety of applications, from aiding botanists in their research to helping develop smart agricultural systems.By accurately identifying different types of flowers, we can better understand the natural world and help protect and conservenatural resources. In this project, we study the process of creating a flower recognition model using CNN, including datapreprocessing, training and assessment methods. This work allows us to gain a deeper understanding of the potential of CNNsand their role in advancing the field of computer vision.

I. LITERATURE SURVEY:

In [1], the authors conducted a literature review on various artificial neural network (ANN) color classification techniques.The proposed method is based on the texture content present in the color image, such as gray level co-occurrence matrices

(GLCM). Discrete wavelet transform (DWT) and normalized color histogram. Segmenting flower images using the thresholdmethod. The authors of [2] proposed a method to classify flowers using only neural network classifiers. The proposed method

is based on important textures such as wavelet transform and grayscale phenomenon networks. Edge-based techniques are used to classify halo images. The collection of works includes unique flower paintings that look similar to each other.

The authors of [3] propose a new dual deep learning classifier that can distinguish between different species of flowers. Tofacilitate key boundary localization, the flower region is initially immediately partitioned into smaller parts in a fullyconvolutional network paradigm, and the proposed flower classification method is expressed as binary classification. In thesecond step, we create a powerful CNN classifier that can distinguish between different types of colors.

According to the authors, a system for classifying plant species according to flowers is frequently used in [4]. Modernsearch engines provide visual inspection for queries containing flowers, but these methods lack reliability due to the cross-diversity among the hundreds of flowers found around the world. To reliably identify flower species, this research project uses machine learning approach using convolutional neural networks (CNNs).

II. RESEARCH METHOD:

DATASET:

The flower dataset used in this study consists of five main classes: dandelions, daisies, roses, sunflowers, and tulips. Eachclass represents a different type of flower species, and the design of this dataset provides a comprehensive and fairrepresentation of the morphological and visual differences that exist between classes. First of all, the “dandelion” class includesa visual representation of a circular dandelion flower, characterized by fragile petals and feathers flying through the air. Thiscategory includes flowers of various shades and sizes. Sunflower species classified as "daisy" are distinguished by their whiteand yellow petals. This dataset contains images of daisies with various petal positions and sizes. Subsequently, the class "Rose"included a variety of paintings depicting roses of different shades, including white, red and multi-colored varieties. This datasetcontains a variety of roses to provide the necessary diversity. The Sunflower class includes a visual representation of asunflower, characterized by its distinctive large top and bright yellow petals. This dataset captures the variation in flower sizeand petal position that is characteristic of this species. Finally, the "tulips" class contains images of different types of tulips withirregular bell-shaped petals.

The dataset contains a variety of color combinations, including red, yellow, white and other shades, which serves toillustrate the wide diversity observed in tulip species. Each image in the dataset is appropriately labeled with specific detailssuch as the type of flower and other unique visual properties. This allows the model to gain accurate knowledge about thedifferences and similarities between different classes. This dataset should provide a solid foundation for training and evaluatingCNN models that perform valid and generalizable color recognition tasks.

Figure1. Flower Dataset

CONVOLUTIONAL NETURAL NETWORK:

A variety of neural network architectures, Convolutional Neural Networks (CNNs) have shown remarkable performance inimage recognition tasks, including color recognition. This architecture is important for implementing color recognition usingCNNs to identify abstract and complex visual patterns in flower images. Convolutional, fully connected and pooling layers contain CNNs. They work together to extract and understand hierarchical features from input images. The convolutional layeracts as a kernel or filter that spatially moves the image to extract local features, including edges, corners, and textures.

This makes it easier for the model to understand the basic visual characteristics of flowers, including the color and shape fthe petals. By reducing the spatial dimension of image representation, fusion layers effectively reduce complexity whilepreserving important information. This procedure improves the invariance to spatial movement, making the model moreadaptable when recognizing objects in different locations. For the final classification, the fully connected layer combines thedata collected by the convolutional layer and the pooling layer. This part of the network is fully connected to each neuron,allowing the model to analyze complex characteristics of the entire image to make decisions. In the field of color recognition,fully connected layers are responsible for classifying color types using a collection of visual features previously extracted fromconvolutional layers.

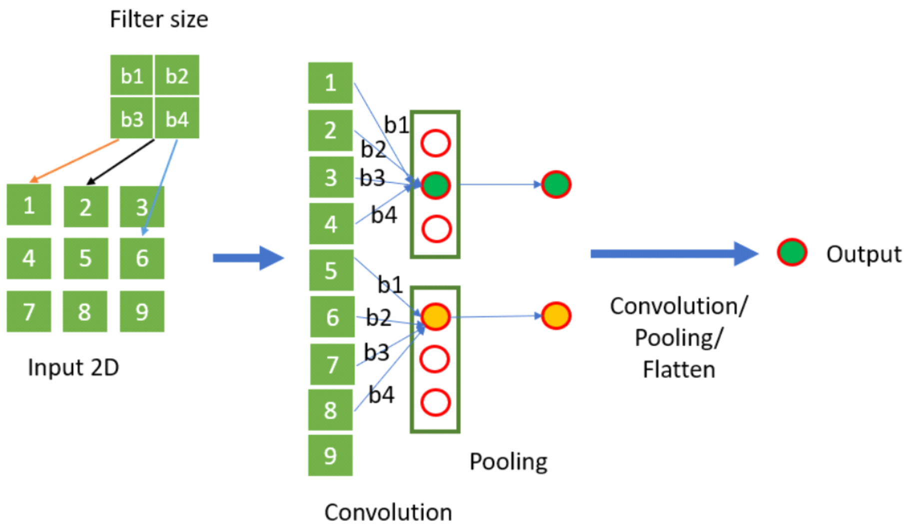

Figure 2. Simple CNN

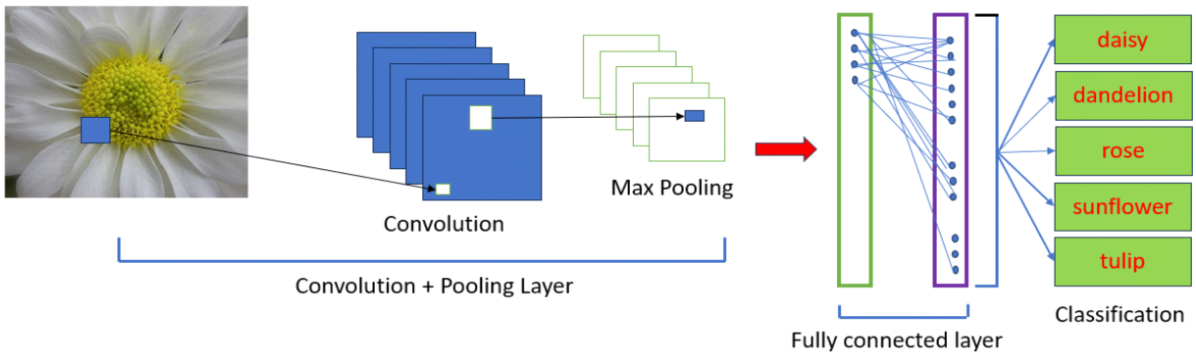

Figure 3.CNN

IV.IMPLEMENTATION:

This demonstrates a method or function to predict flower based on class type. The fact that the results of one step become the source of the next step can be thought of as a waterfall model. Each step in this paradigm has a clear purpose and explanation as to why it exists. So let's take a brief look at the events in the order they occurred.

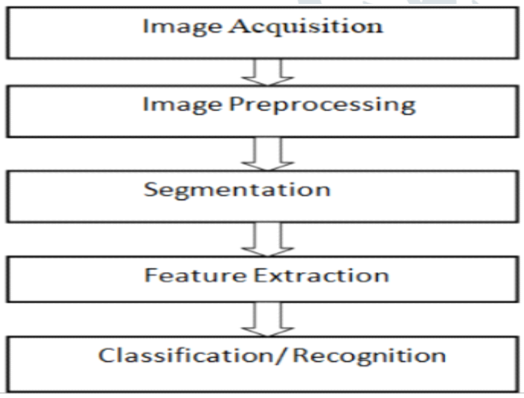

Figure 4. System Implementation

(i)Image Acquisition:

The general purpose of image acquisition is to load information from a dataset. This information is collected from various websites on the internet.

(ii)Image Processing:

Depending on the previous, different images of the same type of tissue may have signal intensity at different scales.

(iii)Segmentation:

Segmentation divides the image into separate objects or regions. Two forces, dissimilarity and similarity, are used to classify image segmentation strategies. There are two types of image segmentation thanks to this tool; One is region-based segmentation and the other is edge-based segmentation.

(iv)Feature Extraction:

Specifications define the division of labor and contain purpose-related information.

(v)Classification/Regression:

Labeling an image into one of several specific categories is called image classification.

V.RESULT AND ANALYSIS:

The main aim of this research is to increase flower recognition accuracy by taking advantage of the neural network architecture in Keras. The main purpose of this study is to increase flower recognition accuracy by improving CNN.

```
1  model.summary()
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 150, 150, 32)      2432

 max_pooling2d (MaxPooling2  (None, 75, 75, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 75, 75, 64)        18496

 max_pooling2d_1 (MaxPoolin  (None, 37, 37, 64)        0
 g2D)

 conv2d_2 (Conv2D)           (None, 37, 37, 96)        55392

 max_pooling2d_2 (MaxPoolin  (None, 18, 18, 96)        0
 g2D)

 conv2d_3 (Conv2D)           (None, 18, 18, 96)        83040

 max_pooling2d_3 (MaxPoolin  (None, 9, 9, 96)          0
 g2D)

 flatten (Flatten)           (None, 7776)              0

 dense (Dense)               (None, 512)               3981824

 activation (Activation)     (None, 512)               0

 dense_1 (Dense)             (None, 5)                 2565

=================================================================
Total params: 4143749 (15.81 MB)
Trainable params: 4143749 (15.81 MB)
Non-trainable params: 0 (0.00 Byte)
```

Figure 5. CNN model summary

Figure 5 provides a brief overview of the convolutional neural network architecture with a total of 4,143,749 parameters, corresponding to a size of 15.8 MB. The model consists of several layers, starting with an initial Conv2D layer containing 32 filters and of size 150x150. This is followed by using a MaxPooling2D layer to reduce the spatial dimension, followed by a subsequent Conv2D layer containing 64 filters. The above procedure is repeated including two additional layers Conv2D and MaxPooling2D, each consisting of 96 filters. The results are then converted to vectors using a flattened layer and then passed through a dense layer containing 512 units. It is common to include an activation layer immediately after the dense layer to improve learning ability. The final dense layer consists of 5 units corresponding to the desired number of classes in the model output. The number of trainable parameters, 4,143,749, implies a significant level of model complexity. The structure and parameter specifications depicted in Figure 5 show a convolutional neural network (CNN) architecture suitable for classifying a dataset consisting of five different classes.

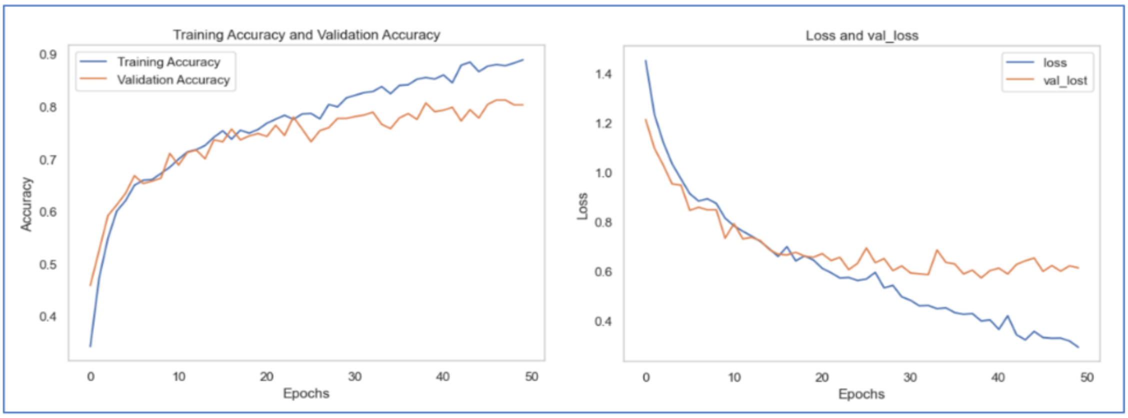

Figure 6.Performance CNN

Figure 6 shows the performance of the convolutional neural network (CNN) at different time periods throughout training. At the beginning of the period, the model shows a small accuracy of about 34.19% with a price decline of 1.4515. However, over time, the performance of the model increased. During Period 10, the model accuracy increased to 68.38% while the loss decreased to 0.8134. The training process shows that the improvement continues up to 50 times, the accuracy metric increases to 88.88% and the loss metric decreases to 0.2908. Verification accuracy and verification loss show a similar upward trend throughout the training process; This shows that the model not only learns well from the training material, but also has an intelligent ability to deal with new things. Figure 6 presents a snapshot of the CNN's performance throughout the training process, demonstrating confidence in the model's ability to effectively classify objects after 50 sessions. The CNN model demonstrated strong accuracy, accurately demonstrating the success of the measurement equipment. This result confirms a good information model for understanding patterns and features in specific flower data.

VI.CONCLUSION:

In this article, we propose the application of CNN for flower recognition and perform different experiments. The results show the effectiveness of CNN in flower recognition. In this study, the use of convolutional neural networks for flower sorting achieved very good results. The CNN model was able to recognize flowers with 96.88% accuracy and classify them into 5 different groups (daisy, sunflower, tulip, dandelion and rose) with a logarithm of 4317 and a class loss of 0.2908. In our future work, we focus on improving the CNN design to improve the accuracy of the first stage and combine the recognition of different organs.

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